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Conference Abstract

Hybrid Scenarios for Biological Identification: Combining Symbolic and Connectionist AI

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Abstract

In the 1970s–1980s, artificial intelligence (AI) generated research and debate, especially around *expert systems* (Fig. 1) to transfer expertise in fields such as medical diagnosis (e.g., MYCIN, Buchanan and Shortliff 1984), industrial troubleshooting, and biological identification. These approaches, focused on knowledge representation and logical reasoning, forming what is now called symbolic AI (S-AI).

The knowledge base (KB) management system Xper was conceived in that context (Lebbe and Vignes 1988). Its current version, Xper3 developed with modern web technologies, builds a KB including a matrix and rules, used by deductive-abductive reasoning (Fig. 2). Like other tools (e.g., Lucid, Delta, Clavis), it allows taxonomists to publish online, interactive identification keys. IKBS (Iterative Knowledge base system, Conruyt and Grosser 2007) uses a structured descriptive model and specimen descriptions as examples of the taxa, then induction allows building of a dynamic decision tree.

Over the last decade, identification has been profoundly renewed by citizen science, the proliferation of automatic visual or acoustic sensors, and the rise of connectionist AI (C-AI), derived from neural networks. This data-driven AI learns from examples rather than

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from explicit logical rules, operating in vector spaces rather than symbolic structures. It has revolutionized taxonomic identification—as illustrated by tools like PI@ntNet or BirdNET. However, C-AI suffers from two main limitations: its need for large annotated training datasets and its lack of explainability (e.g., ability to cite diagnostic characteristics that make up identificaton decisions).

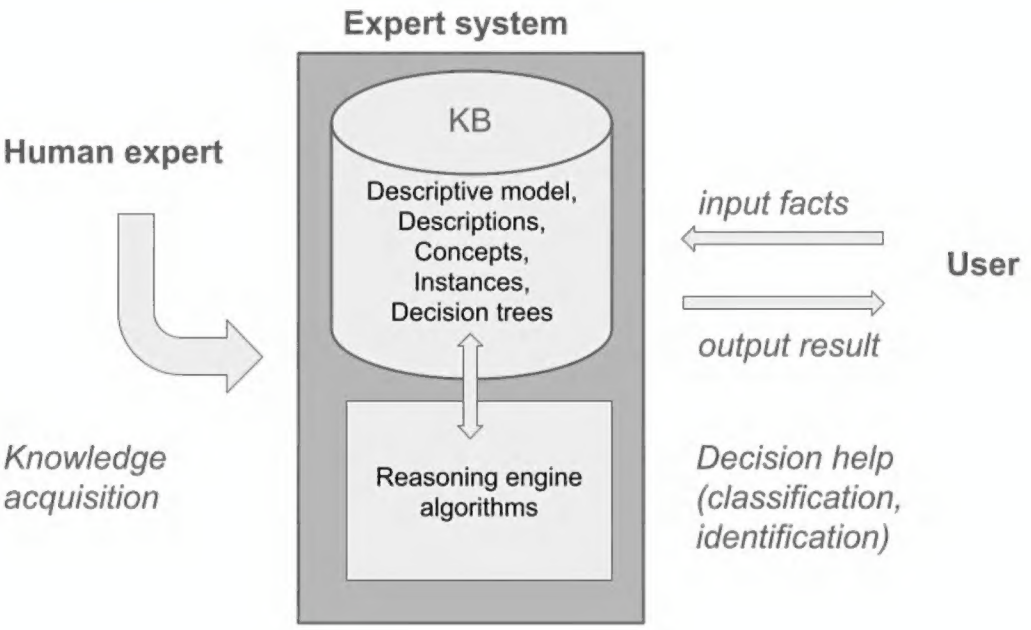

Figure 1.

General architecture of an expert system: the knowledge base (KB) includes structured data, knowledge and rules which are then used by the reeasoning engine. CC-BY R. Vignes Lebbe

	xper	ikbs
Knowledge representation	Matrix + rules	Graph + decision tree
Objects	Taxonomic concepts	Specimen instances
Logical reasoning	Deduction + abduction	Induction + deduction

Figure 2.

Two types of symbolic AI tools with different reasoning. Xper3 uses structured descriptions of taxa; IKBS is based on set of examples to describe each taxon. CC-BY R. Vignes Lebbe & N. Conruyt.

Hybrid approaches combining S-AI and C-AI are now emerging to combine their strengths and mitigate their weaknesses. Building on our long experience with S-AI, we propose three hybrid identification scenarios implemented or envisioned within the Xper3 and IKBS environment.

Hybrid identification scenarios

Our three scenarios assume that users provide one or several images of a biological specimen to be identified (Fig. 3).

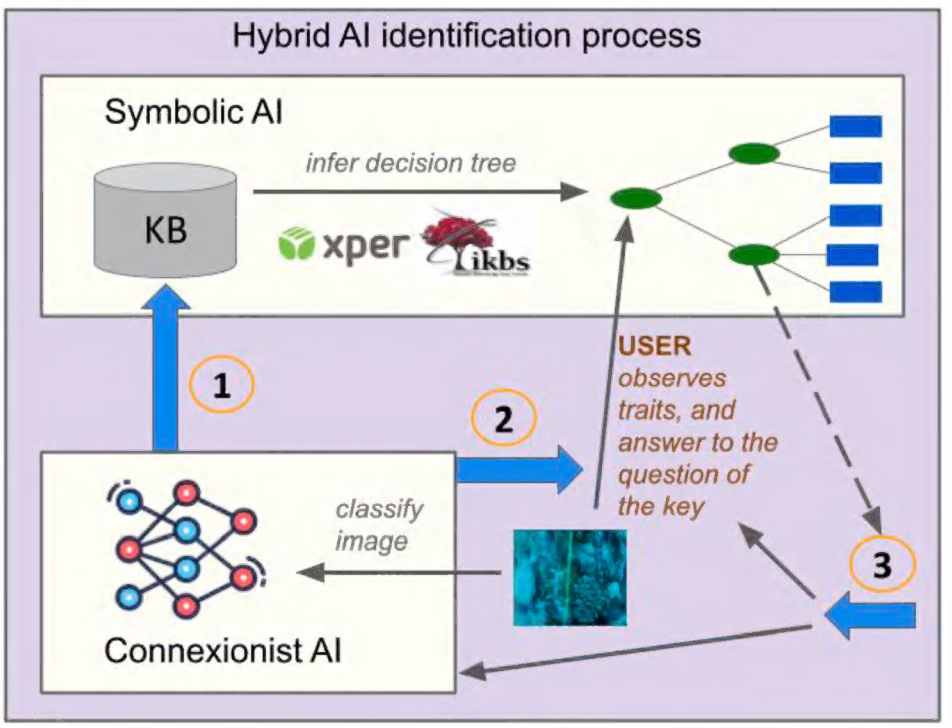

Figure 3.

Three hybrid scenarios: (1) Connexionnist AI filters Knowledge Base (KB) for Symbolic AI; (2) Connexionnist AI resut is compared to user inputs ; (3) the hybridization is used to select a human or automatic (connexionnist AI) answer to progress in the identification key. CC-BY R. Vignes Lebbe.

- **Scenario 1** In Xper3 and IKBS, users freely navigate through a graph or interactive key. In this first hybrid approach, a Convolutional Neural Network (CNN) pre-filters the search space before symbolic reasoning starts and so it targets the decision tree. Depending on the case, it can reduce either the number of taxa considered or the list of relevant characters, by classifying images into higher-level categories such as genera, morphotypes, or morphological traits. With Xper3, the CNN confidence scores are translated into weights within the KB, lowering irrelevant taxa or descriptors.
- **Scenario 2** Here, the AI acts as an assistant verifying the user's inputs. If the CNN detects an inconsistency between the user's path in the key and the descriptions stored in the KB, the system issues a message such as *"Please verify your answer"* and provides complementary explanations or illustrations. The CNNs, trained on broader taxonomic groups than the final species level, make training easier while still providing useful feedback.

- **Scenario 3** When several identification tools coexist (CNNs, Xper3 keys, IKBS keys, etc.), we propose a third scenario with a dynamic interaction between AIs. The hybrid system selects the most appropriate tool at each step, according to metadata describing the domain and performance of each tool. This scenario is currently explored in a project on coral reef monitoring from video transects (Ouassine et al. 2025) with a CNN trained to recognize morphogroups, Xper3 KB at genus rank, and an IKBS KB at species rank.

Discussion and conclusion

In identification, quality and interpretability are more important than speed, but experts are scarce. C-AI is therefore valuable to complement expert work, despite the heavy effort required to prepare training datasets and validate models. Hybridization aims to:

- reduce expert involvement when possible,
- decrease user errors during key navigation,
- and preserve explainable results through symbolic reasoning.

C-AI can further complement S-AI upstream by facilitating the construction of KBs through automatic extraction from fauna and flora, for example.

Hybridisation also allows a frugal use of AI. Moreover, hybrid systems keep humans in the loop—users remain active participants who can learn from the explicit reasoning provided by S-AI.

Further hybrid developments are foreseen. Heatmaps (Selvaraju et al. 2017) could highlight informative image areas to guide users during observation. Large Language Models (LLMs) are already used to extract knowledge from floras or faunas (Nainia et al. 2024) and could soon improve interaction by rephrasing key questions and explanations in natural, multilingual language. Hybrid AI research is still in its infancy but already opens a wide range of perspectives for biodiversity studies and biological identification.

Keywords

expert system, Xper3, IKBS, hybrid AI

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Conflicts of interest

The authors have declared that no competing interests exist.

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